Pong Game Using AI

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Abstract- Pong is a simple game. It can provide AI to a computer. Model reaction time, which waits some period of time before making decisions, Two-part strategy: model accuracy, in which the computer knows exactly where the ball will land, and adding a random error factor to pretend that the computer is fallible. In this paper, try to balance the game by making the computer's skills better if it starts losing, or by making it worse if the computer is dominating. It's easy to play Pong. It can give a computer AI. Model precision, where the computer knows precisely where the ball will land, and adds a random error factor to simulate that the computer is imperfect. Model response time, which waits a certain amount of time before making choices. In this work, balance the game by improving the computer's abilities if it starts to lose or making them worse if it is winning.

Key words: Artificial Intelligence, Visual force, Native state space, Optimized state spaces.

I. INTRODUCTION

Modern learning techniques have been significantly affected by the rise of learning games in recent years [1]. Numerous studies have shown that playing games gives students "mental exercise" and that game-related activities increase students' motivation and foster a variety of crucial abilities [2]. Using learning techniques, it is hoped that an AI player would be able to train on a collection of states with various definitions and come to understand the PONG GAME's environment. After finishing the practise set, the player can keep playing as long as they go without getting struck. The number of training runs, learning rate, discount factor, and other characteristics may be used to evaluate the effectiveness of the learning process. According to the industry, AI allows for more interaction between the player(s) and the game. According to academics, games are great test settings for developing AI methods. There is a yearning for better, more lifelike video games that provide higher levels of enjoyment and realism.

A- AI AS THE PLAYER

- Current thread in research.
- Creating AI that interacts with the game in the manner of a human player.
- “Seeing” the game world.
- “Pressing” keys.
- External to the game environment.
- No cheating.
- A robot without the physical robot.

B- AI AS THE CREATOR

- New trend in both industry and academia.

- AI techniques used to control the game.
- Content creation.
- Adapt levels to suit players ability (Infinite Mario).
- Create weapons based on player tastes (Galactic Arms Race).
- Scene Management.
- Control flow of game to enhance replay ability and maintain a predetermined pacing (Left4Dead).

II. RELATED WORK

There has been a great deal of research done on the use of digital games for learning, with some studies concentrating on the game mechanics and others on instructional strategies that might improve teaching and learning. It is well known that playing digital games encourages students to learn how to collaborate, solve problems, communicate, and experiment—skills that are essential for success in a culture where information is constantly changing [2]. In contrast to practising on a single type of problem, skills acquired through gaming are more likely to transfer, which results in the knowledge and skills becoming automatic and consolidating in memory, allowing the learner to start paying conscious attention to understanding and using new information [3]. Digital games for learning put the player in charge of making decisions by putting him through increasingly difficult tasks and achieving learning through trial and error methods [4]. Digital games, which were first created for fun, have been shown to be helpful for the development of cognitive, behaviour, and social abilities [5]. There is a growing amount of research on the potential advantages of digital games for cognitive development (such as faster information processing [6]), but there is little evidence on how the stage of game play and level of competence influence mental effort. The use of digital games in formal and informal learning environments is now supported by a number of principles [2]. Furthermore, in game design and games' capacity to alter viewpoints and conduct [4], In previous studies on mental effort, electroencephalography (EEG) has been used to monitor participants during game play by measuring changes in their brain activity [7], [8] in order to increase neural efficiency when doing certain tasks [9], [10]. Its may see changes resulting from changes in external perception in the topographical categorization of the electrical activity in the brain [8]. These variations in the activity of various brain bands and zones allow us to deduce cognitive functions like attention and focus, which are essential while playing digital learning games [8], [11].

III. DIVERSE APPROACHES TO STATE DEFINITIONS

Pong Bird is a continuous and dynamic game with an unpredefined environment, this gaming approach pits learning against search methods in an effort to construct an agent that can successfully complete the game's first learning phase. Because it constructs a policy before managing the states it will oppose throughout the game, the Q-learning method is the one that best fits our situation. It is necessary to define the problem's state space in order to facilitate successful learning. The following list of state definitions includes a variety of viewpoints:

Visualforce and Definition: GR – The parameter we utilised to quantize the game grid was grid resolution. GR values of 1, 2, and 4 were employed. In the findings section, we go into greater detail about it.

Native state space;- The state vector's different elements' ranges are as follows:
Vertical: ~ 0 – 500
Horizontal: ~ 0 – 300
Velocity ~ -9 – 9
(Units for the velocity are pixels and pixels per frame.) It is clear that the state space is larger than 10, which indicates that learning would take too long if we used all of the data from the six states. Accordingly, we chose to apply a variety of space quantization techniques.

Optimized state spaces:- Its choose to employ 4 distinct strategies in an effort to reduce the number of states:

- Using only the vertical and horizontal distances,
- Horizontal relativity and vertical distance
- Vertical distance and horizontal relativity
- A Boolean indication of whether velocity and distance are positive or negative.

In order to further reduce the size of the state space, we established the maximum and minimum distances between pipes after testing each distance with various GR values. We count it as the upper-lower bound of the distance outside of this range.

Its obtained new state space sizes for each technique (corresponding to the approaches above) after all those reductions:

- Vertical Distance ·horizontal Distance/ GR 2.
- 2·Vertical Distance/ GR.
- 2·20·Vertical Distance/GR.
- 2·Vertical Distance ·horizontal Distance/ GR 2.

I made the decision to test out each of those 4 ways to see which one promotes the most effective learning.

Rewards :-

Staying alive between states: 1Dying: -1000.
Scoring +1: 1000.

How Game Work?

Generally speaking, a game's primary execution is divided into iterations by means of a loop that runs continually.

- Games that are constructed from discrete ticks, much like film.
- Each iteration.
- Takes player input.
- Determines the gameworld's new state.
- Shows a new state on the screen.

How to Use the Code

Python 3.6 is the platform we employed. We tried it on a 64-bit Python. In order to create the learning agents, we defined a new game engine based on the open source Pong Bird game.

Files Game.py: It defines a class of abstract games.

PongGame.py: This describes the game Pong.

AgentPongGame.py: Uses an agent to extend the Pong game.

Agent.py: Its uses an agent to extend the Pong game. Different agent classes and state classes are defined.

Main.py: A programm for manually adjusting the game's settings.

TestScript.py: Pong games are executed with agents that have different parameter combinations.

Running the game: Install the pyGame library, please (pip install PyGame). Ensure that the easy GUI library is set up (pip install easy GUI) so that the game may be launched with only one set of settings: Main.py in Python.

Parameters and ranges:

Training runs: The episodes required before the agent quits learning. When the bird strikes the pipe, the episode is over. The likelihood of selecting a random action is known as the exploration rate (Epsilon). 0-1.

Learning rate (Alpha): A new Q-mass with a value of 0-1.

Discount factor (Gamma): The element that increased the cumulative prize. 0-1.

Pipe vertical gap: The separation between the lower and upper pipes is 130-160.

FPS: The game will play more quickly the more frames it has. whichever of the natural numbers.

Agent: True if a learning agent is used. False if human players are used.

GR: 1, 2, and 4 are as described in the section on approach.

Datatype: type of state space definition to use:

- 1: Naïve approach.
- 2: Distance only.
- 3: Horizontal relativity and vertical distance.
- 4: Horizontal relativity and vertical distance with bird velocity.
- 5: Horizontal relativity and vertical distance with binary bird velocity.

Agent Mode: In order to complete the learning phase (much) faster, the game starts in agent mode without the GUI interface. There is a set of keys to press (not those on the NUMPAD) in order to switch the GUI mode (in game):
0: no GUI mode - speed is only limited by the processing power.
- 1: 30 FPS
  - 2: 60 FPS
  - 3: 120 FPS
  - 4: 240 FPS

Human Mode: The space key is the sole key required for leaping and starting a game.
Output: Every 50 episodes, the user will get a message throughout the learning period. The top score and average score from the previous 50 episodes are included in the message.

IV. HYPOTHESES

Its address four primary hypotheses in the current work. The first looks into whether players who perform well in the game have more EEG band power modulation. We estimate that better performance will result in more processing and activity, which will enhance game activity and EEG band power modulation. The second hypothesis looks at whether players who are more skilled in the game exert more mental effort. We anticipate that if game activity and engagement both rise with experience, there will be a corresponding rise in EEG-measured mental effort. The other two hypotheses focus on the relationship between mental effort and two extremely popular game-play design aspects, namely the number of attempts/lives and level of difficulty[12].

Players' performance with the game displays a positive relation with their mental effort. When talking about strong achievers, previous research using standardised assessment exams and game scores showed that higher scores in a learning game do not always equate to higher learning outcomes and effort [13]. By exploring this relationship using brain activity, we may thus gain a better understanding of the link between learning and cognitive ability.

Players' experience with the game has a positive relation with their mental effort.Its believe that because those abilities are key drivers of their mental effort, they would lead to an increase in mental effort as players gain experience [14].

Players' "number of lives left" has a positive relation with players' mental effort (the fewer the lives, the higher the mental effort). In learning games, the quantity of attempts or lives remaining is a key design component [15]. Low life totals (or finishing with one life left) are strange situations [16], and earlier game concepts (such as power ups) have been used to enhance learning [17]. However, further research is required to clarify the relationship between the number of remaining tries and the user's mental effort using objective measurements (such as EEG).

The difficulty of the game has a positive relation with players' mental effort (a more difficult game results in higher degree of mental effort). Researchers have found that users' mental effort is significantly influenced by difficulty [18], []; nevertheless, examining and even quantifying this effect can help us gain new design insights.

V. CONCEPT OF GAME AND ITS WORKING METHODOLOGY

Pong is a 2-dimensional arcade tennis sports video game that is depicted in Figure 1 and is developed in Python. This little project is a remake using the beginner-friendly Python language. In terms of gameplay, it is a two-player game that requires the use of a mouse to control both players from opposite sides. When a player fails to contact the ball and it touches another area of the screen, the game is over. A variety of sounds, JavaScript, and HTML were utilised in the creation of this mini-game. While playing the Pong game, players will be upgraded to a more difficult level as it gets harder and harder. The users of this microproject find it simple to use and comprehend.

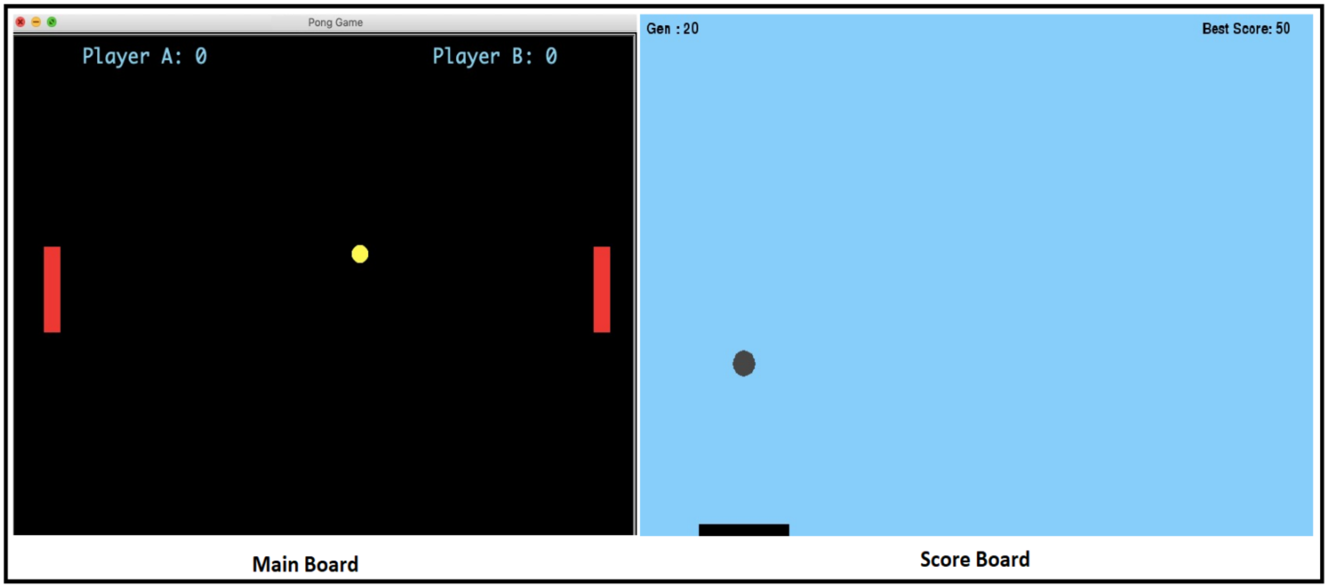

Figure 1: Pong Game

The Game: A controlled experiment concentrating on skill learning was created for this investigation. A phrase with a broad definition, skill acquisition (also known as movement-motor learning [20]) includes both motor adaptation and decision-making [21], [22]. In our study [23], Pac-Man, a time-testing game that has previously been used to gauge particular talents (motor skills), was utilised in our study [23]. In particular, Pac-Man was employed, which offered three lives each session and followed all the rules of the game. The four keyboard arrow buttons were used to control the game. From one session to the next, the game's difficulty rapidly grew.

Participants: In this, recruited a total of 17 participants (7 females) aged between 17 and 49 years (mean = 32.05, SD = 8.84). Participants were recruited from the participant pool of the Norwegian University of Science and Technology in Trondheim. Participants were familiar with the game, but none of them had played the game in the previous 2 years. Prior to completing the tasks, participants were informed about the purpose and procedure of the experiment and of the harmlessness of the equipment. Participants were given a movie theater ticket upon completion of the study, as a compensation for their time.

VI. CONCLUSIONS

Q-Learning works The outcomes clearly demonstrate that an agent equipped with a Q-Learning mechanism is capable of learning the game and achieving results that are superior to those of a typical player. **State space size** It establishes a direct link between the state space's size and the learning time required by the agent. Due to the nature of the Q-Learning algorithm, this is obviously inferred. Additionally, it is the most important parameter (except for the exploration—more on that after this). The learning speed was slower on the bigger state spaces, but it was more constant and monotonous, which is something else we saw. This is because the states are easier to identify when the grid resolution is higher (lower GR factor). The resolution of the actual game doesn't vary with the GR factor; it's always the entire resolution of the game. Thus, on a low-res grid, a good state and a terrible state could be grouped together. **Best** The smallest state space (method #2-distance alone and grid size 4) produced the greatest results. **Exploration During** a frame is a turn and there are many (actually, a lot of) frames in a game, we observed in the experiments that the exploration parameter must be close to 0. The game proved impossible to learn, at least during the time allotted for each run, due to an exploration factor of above 0.0001.

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